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Valuation of travel attributes for using automated vehicles as egress transport of multimodal train trips

M.D.Yap[a,b]*, G. Correia[a], B. van Arem[a]

[a] *Delft University of Technology, department Transport & Planning, Delft, the Netherlands*
[b] *Goudappel Coffeng, Deventer, the Netherlands*

Abstract

In the recent years many developments took place regarding automated vehicles (AVs) technology. In fact AVs are expected to become available on the market in the next decades. It is however unknown to which extent the share of the existing modes will change as result of AVs introduction. To the best of our knowledge this study is the first where traveller preferences for AVs are explored and compared to existing modes. Thereby its main objective is to position AVs in the transportation market and understand the sensitivity of travellers towards some of their attributes. Because there are no fully-automated vehicles currently on the market, we apply a stated preference choice experiment where we explore the role of classic instrumental variables such as different travel time components and travel cost. In our study we focus on positioning AVs in the context of last mile transport at the activity-end in multimodal train trips. We can conclude that first class train travellers on average prefer using an automated vehicle as egress transport between train station and final destination, compared to using other egress modes. Second class train travellers on average prefer the use of bicycle and bus/tram/metro as egress mode instead of automated vehicles. Especially for first class train passengers, implementing AVs as last mile transport therefore has potential. Second, sensitivity of travellers for in-vehicle time is considerably higher for an automatically driven AV, compared to a manually driven AV. As consequence, the willingness-to-pay for a certain travel time reduction in an automatically driven AV is considerably higher, compared to a manually driven AV. Despite theoretical advantages of using travel time more efficiently in an automatically driven AV, it might be that psychological concepts, like attitudes, play a role here. Since automated driving is a very new and innovative way of transportation, the classic instrumental attributes like travel time might not tell the whole story.

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Keywords: automated vehicle; cybercar; last mile transport; preferences; stated choice

* Corresponding author. Tel.: +31 (0)6 22807934.
E-mail address: MYap@Goudappel.nl

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1. INTRODUCTION

In the recent years many developments took place regarding automated vehicles (AVs) technology. In fact AVs are expected to become available on the market in the next decades. It is however unknown to which extent the share of the existing modes will change as result of AVs introduction. To the best of our knowledge this study is the first where traveller preferences for AVs are explored and compared to existing modes. Thereby its main objective is to position AVs in the transportation market and understand the sensitivity of travellers towards some of their travel attributes. Because there are no fully-automated vehicles currently on the market, we apply a stated preference choice experiment where we explore the role of classic instrumental variables such as travel time or cost. In our experiment, we also indicate automated vehicles as 'cybercars'. We use the last mile trips between a train station and travellers' final destination as the object of our study. In multimodal train trips, a relatively high disutility is caused by the access and egress. Hence we hypothesize that by providing AVs as egress mode we may improve the attractiveness of multimodal rail trips and expect a modal shift to the train+AV combination. AVs hereby contribute to improving door-to-door transportation. In our study we thus focus on positioning AVs in the context of last mile transport in multimodal train trips.

2. METHODOLOGY

2.1 Alternatives and attributes

Multimodal public transport trips consist of three stages: access, main part and egress. We define a multimodal PT trip in this paper as a trip where more than 1 mode is used, using a public transport mode for the main part of the trip. For each stage different alternatives are available, such as walking, cycling, private car or PT (bus/tram/metro: BTM) for access; train, metro, tram or bus for the main stage; and PT (BTM), cycling or walking for the egress part. For all these stages different attributes - like in-vehicle time, waiting time, travel costs – are relevant for multimodal mode choice. The high number of possible combinations of mode alternatives and attributes makes it complex to incorporate all those combinations in one stated choice experiment in a manageable way. Capturing the attribute sensitivity for all these combinations would lead to a high number of choice sets provided to each respondent, leading to a too high complexity task for the respondent, or it would require a very large sample of respondents.

In order to reduce this complexity, in our study we focus only on multimodal PT trips where trains are used in the main stage. Besides, we only consider trips going from an origin next to the home-end of a trip to a destination in the activity-end. As Hoogendoorn-Lanser et al. (2006) indicate, there are differences in availability, knowledge and use of multimodal trip alternatives between the home-end and activity-end of a trip. Therefore it is important to explicitly distinguish home-to-activity trips from activity-to-home trips, since attribute sensitivities can be different on each direction of the trip. We then only considered the automated vehicle as egress transport from the train station to the activity-end of the trip. The sensitivity to attributes of the AV as access transport from the home-end origin to the train station is not explored in this study. Furthermore, we clustered attributes and attribute levels for the access and main stage of the multimodal trip together, which means that we provided respondents with attributes and attribute levels for the access and main stage of the trip together, whereas attributes for the egress stage of the trip are mentioned separately (Figure 1). This clustering is in line with our scope of exploring the sensitivity to AV attributes on the egress stage of the trip only. This also means that different modes for the access stage of the trip are not explicitly mentioned in our study (Figure 2). This allows the reduction of the number of alternatives and attributes in the stated choice experiment.

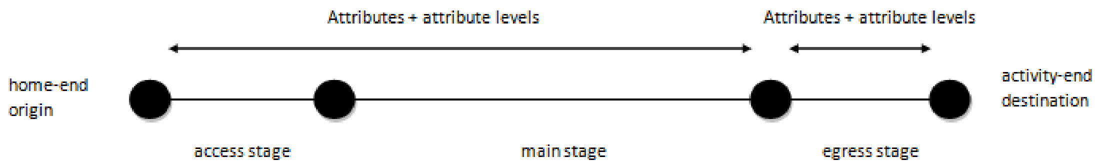

Figure 1. Clustering of attributes for access and main stage of trip; separate attributes for egress trip stage.

The alternative in which walking is used as egress mode is not considered in our study, since we hypothesize that AVs and walking do not serve the same market as egress transport. We expect that AVs will not be used as substitute for walking on the egress stage, given the limited area around a train station which can reasonably be reached by walking. To get insight into the trade-offs between mode alternatives and sensitivity to AV attributes, incorporating walking as egress mode, is therefore not necessary. In this study we included access+train+AV as a multimodal trip alternative next to the two remaining most common existing multimodal trip alternatives: access+train+PT (bus/tram/metro) and access+train+bicycle. In our study two variants in which AVs are used as last mile transport are explicitly incorporated in our study. In one variant, a traveller has to drive the AV *himself* from the train station to the final destination. After reaching the destination, the AV can however drive automatically, without driver, to the next client. We indicate this AV application as a regular car-sharing system as egress transport, since the vehicle will be manually operated during the part of the AV trip where travellers are on board. In the other variant, the AV will always drive automatically without a driver, regardless whether a traveller uses the vehicle as passenger or not. This distinction allows us to investigate whether differences in valuations of attributes of the AV exist in case the vehicle can be driven manually. For these four multimodal alternatives we also distinguished whether a traveller uses the 1st class or 2nd class train carriages in the main part of the trip. This allows gaining insights in the sensitivity of travellers toward AV attributes in relation to the use of 1st class train carriages, which can be of relevance for certain traveller segments like business travellers. This means that in total 8 multimodal trip alternatives are considered, of which in 4 alternatives a form of AV is used for egress. Next to these multimodal alternatives, also a unimodal trip between home-end origin and activity-end destination by private car is incorporated, hence in total 9 different mode alternatives were provided to respondents in our experiment as it can be seen in Figure 2.

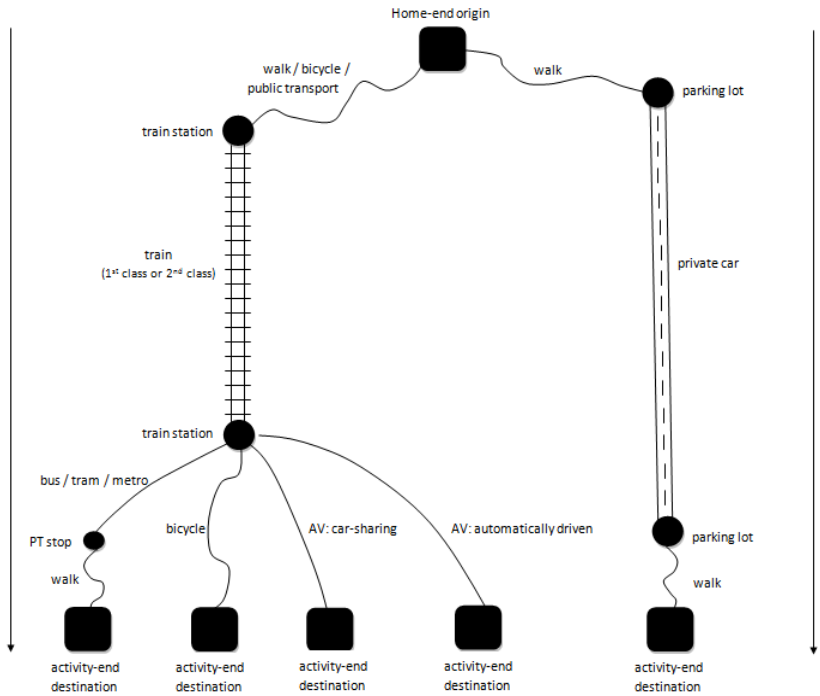

Figure 2. Overview of trip alternatives incorporated in the stated choice experiment. Each multimodal trip alternative can be made using 1st class or 2nd class train carriages.

Table 1 gives an overview of all attributes used in our stated choice experiment, with corresponding attribute levels. For all continuous attributes, three attribute levels are defined in order to enable testing linearity of the part-worth utilities. In the experiment we used instrumental attributes related to travel time and travel costs of different trip components. The used attribute levels for travel time and costs are based on values which hold for average medium-distance, regional trips in the Netherlands and can therefore easily be imagined by respondents (CBS 2013). We assumed no waiting time for bicycle egress. Also, for using bicycle or AV as last mile transport, no walking time is assumed from the place where a passenger stores his bicycle or disembarks the AV to the final destination. This is in line with the door-to-door service foreseen to be provided by AVs in this study. In the survey, walking time for these egress modes is indicated as '0 minutes' in each choice set. In line with European averages, attribute levels for fares for 1st class carriages in trains are 150% of the fares used for 2nd class. There are also costs included for using the bicycle as egress mode since we consider the activity-end of the trip, where personal bicycle availability is usually limited. These costs reflect the possible costs for renting or parking a bicycle at the train station, in line with prices valid for renting a bike at Dutch train stations, which was explained to respondents. For the travel costs for AVs, a distinction is made between the AV fare if a passenger travelled 2nd class or 1st class in the train. In the experiment, we mentioned that a lower AV fare holds if the traveller would use the 1st class train carriages during the main stage of the trip. This allows us to investigate whether improving the last mile transport between train station and activity-end destination can also attract more passengers to the 1st class train carriages. Besides, for AVs we incorporated the discrete variable 'sharing' as attribute, indicating whether a passenger has to share the AV with some other passengers or not. From the survey it is clarified to respondents that sharing the AV does not lead to a probability on making a detour to drop another passenger first at another destination. Only passengers having the same destination are allowed to (possibly) share the AV.

Table 1. Overview of attributes and attribute levels used in the stated choice experiment

Attribute	**Attribute levels**		
Travel time private car (walking time to car + driving time + search time parking space)	25 min	35 min	45 min
Travel time train (travel time access mode + train)	20 min	30 min	40 min
Waiting time BTM egress	5 min	10 min	15 min
Waiting time AV (car-sharing) egress	0 min	3 min	6 min
Waiting time AV (automatic) egress	0 min	3 min	6 min
Travel time bicycle egress	6 min	12 min	18 min
Travel time BTM egress	5 min	10 min	15 min
Travel time AV (car-sharing) egress	5 min	10 min	15 min
Travel time AV (automatic) egress	5 min	10 min	15 min
Walking time private car egress	2 min	6 min	10 min
Walking time BTM egress	2 min	6 min	10 min
Fuel costs + parking costs private car	€5	€10	€15
Travel costs train (ticket access + train) 2nd class	€5	€7.50	€10
Travel costs train (ticket access + train) 1st class	€7.50	€11,25	€15
Travel costs bicycle egress	€0	€1,50	€3
Travel costs BTM egress	€1	€2	€3
Travel costs AV (car-sharing) egress 2nd class	€2	€3	€4
Travel costs AV (car-sharing) egress 1st class	€0	€1	€2
Travel costs AV (automatic) egress 2nd class	€2	€3.50	€5
Travel costs AV (automatic) egress 1st class	€0	€1.50	€3
Sharing AV (car-sharing) egress	No sharing	Sharing with few passengers	
Sharing AV (automatic) egress	No sharing	Sharing with few passengers	

2.2 Choice sets

Given the 9 mode alternatives and attributes mentioned in Figure 1 and Table 1, we used a fractional factorial experimental design to develop choice sets for respondents. A full factorial design would lead to a very high number of choice sets, which either exceeds the number of choice sets one respondent can reasonably answer, or would require a very large sample of respondents (denoted as N) if blocking would be applied. We constructed efficient designs using the software package NGENE (ChoiceMetrics 2012). Efficient designs use prior estimates of the parameters to optimize the experimental design. As long as there is any information about the values of the priors (even if it is only the sign of the parameter estimate), using efficient designs will always outperform the traditional orthogonal designs. Efficient designs aim to minimize the standard errors of the estimates given the prior values. This means that for a given number of respondents the reliability of the parameter estimates increases. Our aim was to minimize the D-error, which takes the determinant of the asymptotic variance-covariance (AVC) matrix (Ω), in order to generate a D-efficient design (X). Note that the D-error assumes one respondent making all choices in the calculations using the AVC matrix (Ω_1) (Bliemer and Rose 2006, Bliemer and Rose 2008, Rose et al. 2008).

We used the estimation results from Arentze and Molin (2013) as input for determining most of our prior values. Arentze and Molin (2013) investigated traveller preferences in multimodal networks in the Netherlands: they estimated coefficients for travel time and costs for different modes separately for access, main and egress stages in multimodal trips. We used their estimated coefficients for the egress trip stage as prior to the attributes in our study related to the egress trip stage. Consistently, we applied main trip stage coefficients from their study as priors for attributes in our study related to the main part of the trip. In Arentze and Molin (2013), no estimates were however available for in-vehicle time coefficients in the automated vehicle, since to the best of our knowledge our study is the first which explores these values. As prior estimates we assumed that in-vehicle time coefficients for automated vehicles equal the in-vehicle time coefficients estimated for private car driving in their study. Since the binary attribute ‘sharing the automated vehicle’ was not included in their study, for this attribute we used the estimated coefficient from Van Zuylen et al. (2010) – a Dutch study focusing on PRT systems – as prior and scaled this to the coefficients estimated by Arentze and Molin (2013). Van Zuylen et al. (2010) In Arentze and Molin (2013), respondents having work or study as trip purpose were however not included in the sample. Also, sensitivity to attributes of automated vehicles was not known on beforehand. This means that there is some uncertainty around these prior parameter estimates for applying in our study. Therefore we generated a Bayesian efficient design which aims to minimize the expected D-error (equation (1)), in order to get a more stable design which is robust to this uncertainty (Bliemer et al. 2008). In this expression, K indicates the total number of parameters to be estimated. Estimates of the priors $\tilde{\beta}$ were drawn from a uniform distribution by quasi random Monte Carlo draws using Halton sequences to approximate Bayesian efficiency (Halton 1960). Lower and upper bounds of the distribution for each parameter are determined by applying -10% and +10% margins around the parameter estimate found in Van Zuylen et al. (2010) and Arentze and Molin (2013).

$$\overline{D - error} = \int_{\tilde{\beta}} \det\left(\Omega_1(X, \tilde{\beta})\right)^{\left(\frac{1}{K}\right)} f(\tilde{\beta}|\omega)\, d\tilde{\beta} \tag{1}$$

In total 12 different choice sets were generated, which were divided in two blocks of 6 choice sets. By providing each respondent only a limited number of choice sets, we aimed at reducing the time needed to answer the survey, thereby increasing the rate of response and representativeness of the sample. Besides, we aimed to prevent a reduced performance of the respondents when answering the choice sets because of distraction, or because of a too high task complexity. The mean Bayesian D-error remained stable having a value of 0.121. By selecting the design with the lowest value for the D-error, we determined the attribute levels for each of the 12 choice sets.

Figure 3 shows an example of one of these choice sets, as it was presented to respondents in the survey. As can be seen from Figure 3, we used a constrained design in order to reduce task complexity for the respondents. For each multimodal trip alternative in the choice set, the attribute levels for the variant using the 1st and 2nd class train carriages were constrained to be equal. For example, in the egress trip stage the attribute levels for waiting time, travel time, travel costs and walking time to destination for the alternative access+train+bus/tram/metro using 1st class train carriages are equal to the attribute levels for the alternative access+train+bus/tram/metro using the 2nd class train carriages (see the left column in Figure 3). Moreover, the attribute levels for travel time and travel costs of the main part of the trip were constrained to be equal for all alternatives which use train as main travel mode. This way, respondents were able to make clear trade-offs between attributes, while not being provided with too much variety in too many attribute levels simultaneously. In the general introduction of the stated choice experiment in the survey, Figure 2 was shown to respondents. By designing the choice sets as shown in Figure 3 with a similar presentation of the alternatives and attributes, we intended to provide as much clarity as possible to the respondents in a type of experiment that is prone to mistakes. Rose and Hensher (2006), Hensher and Rose (2007) and Hensher et al. (2011) show with their studies that respondents are able to understand and answer relatively complex choice sets, as long as these choice sets are meaningful and can be easily imagined. In every choice set it was clearly stated to respondents that they had to imagine a trip *from* home *to* a certain activity, in order to safeguard that the attributes for the egress trip stage were related to the activity-end of the trip.

2.3 Survey

For our study we designed an online survey. After a general introduction about automated vehicles and their role as last mile transport for PT trips, this survey consists of three parts. In the first part, some general characteristics about the regular trips made by the respondents were questioned in order to introduce respondents to the topic. Automated vehicles and their role as last mile transport for PT trips were introduced in a brief and objective way. In the survey, AVs were introduced by using the italic text below, including two pictures:

"Over the last years, many developments took place regarding vehicles which are able to drive partially, or even fully automated. A vehicle which is able to drive fully automated, without driver intervention, is called a cybercar. One of the possible applications of such a cybercar is to increase the attractiveness of the door-to-door journey for which train is used as main mode of transportation. The cybercar would then be used for egress between the train station where a traveller leaves the train and the final destination of the journey. When a passenger leaves the train, the cybercar is waiting near the station for the transport to the final destination. This 100% electric vehicle always supplies a direct, non-stop connection to the final destination and always stops direct in front of the destination. The cybercar can also be used to travel back from an appointment to the train station. During a trip the cybercar can be accessible only for you as traveller (with a possible travel partner), or the cybercar has to be shared with a few unknown fellow travellers having the same destination".

The second part consists of the stated choice experiment. In this part, first the experiment and the attributes were explained. A figure similar to Figure 2 was shown to respondents to explain the available alternatives and attributes in the multimodal trip. Then, 6 choice sets were presented to each respondent. Each choice set was presented to respondents in a manner similar to Figure 3. Each respondent was assigned randomly to one of the two sets of 6 choice sets, so that in total all 12 choice sets of the experiment were answered by an equal number of respondents. The third part of the survey contains questions about the socio-economic status of respondents.

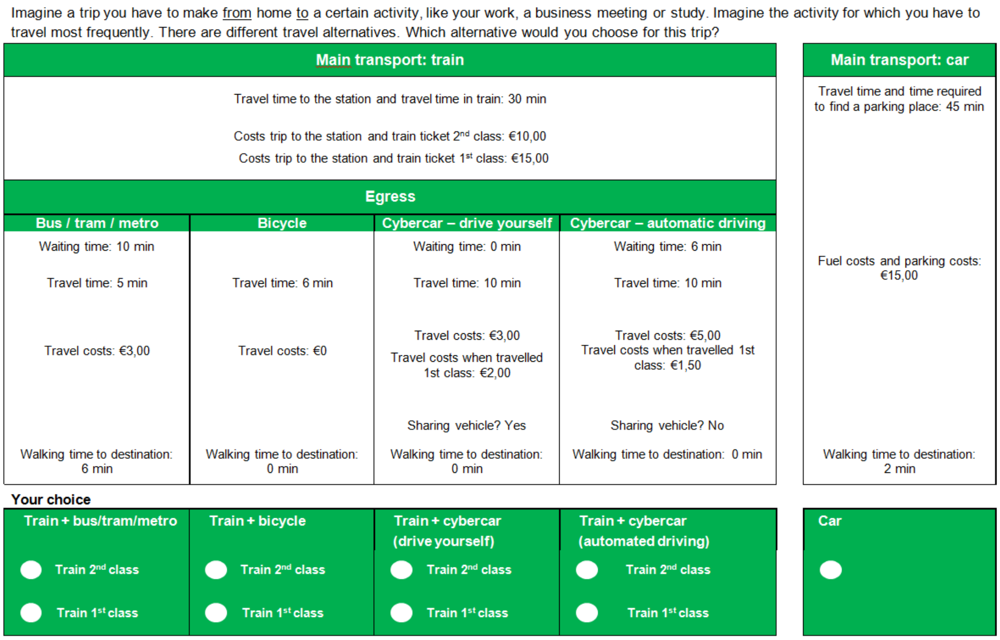

Figure 3. Example of choice set as provided to respondents in survey

A large national online panel in the Netherlands was used for gathering respondents for the designed online survey. Only respondents older than 18 years were allowed to answer the survey. Besides, only respondents who travelled at least twice a month on average could answer the survey. By this selection we made sure that respondents had sufficient experience with travelling in general to understand the different attributes in the stated choice experiment. The sample was meant to be as much as possible representative of the Dutch population of travellers regarding different socio-economic variables. Some respondent segments were slightly oversampled when distributing the online survey, based on the historic statistics of non-response per segment. For example, since historic data in the online panel showed that non-response of male respondents is higher than non-response of female respondents, males were slightly oversampled. An interlocked stratification procedure was applied for the segments gender and age aiming at obtaining a distribution of respondents regarding gender and age in the sample which is as much representative for the Dutch population as possible. In total, 1,149 respondents started the survey, of which 1,053 (91.6%) completed all questions. Further checking the reliability of answers of respondents led to the exclusion of 292 respondents (28%), leading to a remaining sample size of N=761 respondents. After comparing socio-demographic statistics from our survey with national statistics of the Netherlands, we can conclude that the sample is sufficiently representative of the population.

2.4 Model specification and estimation

In order to explore preferences of travellers for using automated vehicles, the following model was estimated. We used a utility maximization framework in the specified model, where we assumed that each individual chooses a certain alternative m if the utility $U_m > U_{n \neq m}$. For each of the 9 alternatives m included in the choice sets, the utility function as presented by formula (2) is estimated from the observed data.

$$U_m = \beta'_x x_m + \varepsilon \qquad (2)$$

In this formula β'_x is a $[K\ x\ 1]$ vector which represents the importance of all instrumental variables x included in the alternative specific utility function U_m. $\beta'_x x_m$ forms the structural utility component, which is specified to be linear-in-parameters. ε is the i.i.d. error component of the utility function, which reflects the unobserved part of the utility function. In this model, the instrumental attributes as mentioned in Table 1 and Figure 3 are included in the structural utility component. This means that this model is estimated based on attributes which were provided in the stated choice experiment only. Different coefficients are estimated for different travel time components, and for in-vehicle time in different modes, in different trip stages and in different train classes. For travel costs a generic coefficient is estimated. Assuming that the error component of the utility function follows an extreme value type I distribution, a standard multinomial logit (MNL) model could be estimated. Since we focused on exploring sensitivities to AVs and exploring how to position AVs in the transportation market, our aim was not to estimate the best fitting, most complex model. Therefore we only estimated standard multinomial logit models in this research. We applied maximum-likelihood estimation to determine the values of the coefficients, given the stated choices made by respondents, using Biogeme as software package (Bierlaire 2003).

3. RESULTS

In Table 2 we show the estimation results of the final estimated discrete choice population model. This model has an adjusted Rho-Square of 0.20 and a final log-likelihood of -7,997. Based on 4,566 observations, in total 29 parameters are estimated. We used robust t-values in order to correct for panel effects. Only coefficients having a p-value < 0.10 are incorporated in the population model. Since it is an exploratory study, we used a relatively high threshold for the p-values because it is also important to identify the sign of the relation between the explanatory variables and the choice for the AV. In our estimations we applied effect coding for all attribute levels, for which the constant of each alternative reflects the average utility over all choice sets. The estimated marginal values for each attribute level represent the contribution of each attribute level to the total utility, expressed as the deviation from the average utility. The unimodal car alternative is used as base alternative, to which the estimated values of the other alternatives are expressed, of which the utility is fixed equal to zero. All continuous instrumental attributes are incorporated with three attribute levels, so that linearity can be tested. This means that for each of these attributes two indicator variables are used where the highest attribute level is coded as {1 0}, the middle attribute level as {0 1} and the lowest attribute level as {-1 -1}.

Table 2. Estimation results of final discrete choice model

Parameter	Value	T-value	P-value
constant_car	0.00		
constant_1train_btm	-3.74	-23.3	0.00
constant_1train_bicycle	-2.97	-26.0	0.00
constant_1train_cybercar-manual	-2.71	-25.9	0.00
constant_1train_cybercar-automatic	-2.88	-26.4	0.00
constant_2train_btm	-0.96	-19.0	0.00
constant_2train_bicycle	-0.62	-14.2	0.00
constant_2train_cybercar-manual	-1.54	-19.4	0.00
constant_2train_cybercar-automatic	-1.59	-16.9	0.00
in-vehicle-time_car1	-0.14	-3.65	0.00
in-vehicle-time_access+first_class_train1	-0.21	-3.20	0.00
in-vehicle-time_access+second_class_train1	-0.27	-6.44	0.00
in-vehicle-time_egress_btm1	-0.11	-2.23	0.03
in-vehicle-time_egress_bicycle1	-0.23	-5.12	0.00
in-vehicle-time_egress_cybercar-manual1	-0.17	-2.97	0.00
in-vehicle-time_egress_cybercar-automatic1	-0.29	-5.92	0.00
waiting-time1	-0.20	-6.69	0.00
walking-time1	-0.15	-4.76	0.00
travel-costs1	-0.38	-17.8	0.00

In Table 2, for each attribute consisting of N attribute levels, the corresponding indicator variables are numbered from 1 to $N-1$. The last number of the parameter name represents the number of the indicator variable. Regarding the constants, all multimodal trip alternatives are valued more negative compared to the unimodal car alternative. This can logically be explained because multimodal alternatives require at least two transfers, often longer travel times and less comfort and privacy compared to a private car alternative. For first class multimodal trips, trips with AV as egress are on average valued less negatively (manual: -2.71; automatic: -2.88) than trips using bicycle (-2.97) and bus/tram/metro (-3.74) as egress. Manually driven AVs as egress are valued slightly less negatively than those automatically driven by first class train travellers. For second class multimodal trips, AVs as egress are valued somewhat more negatively (manual: -1.54; automatic: -1.59) than trips made by bicycle (-0.62) and bus/tram/metro (-0.96) as egress. Manual and automatic driven AVs are almost similarly valued by second class train travellers.

For in-vehicle time of different modes, only the first indicator variable showed to be significant. This shows a linear relation between in-vehicle time and utility. Marginal values for in-vehicle time for access+main trip stage with first class train travelling in the main trip stage are lower (-0.21) than for alternatives with second class train travelling in the main trip stage (-0.27). Marginal values for in-vehicle time in a manual operated AV (-0.17) are considerably lower than in automatic AVs (-0.29). From a theoretical perspective it might be hypothesized that the value of time in an automatic AV is lower compared to a manually driven AV, since passengers can spend their travel time doing other things (like using their phone, mailing, working). Our empirical results however show that the in-vehicle time valuation in automatic AVs is lower than in manually driven AVs, despite this theoretical advantage of automatic AVs. Comparing the in-vehicle time valuation of different egress modes, results show that in-vehicle time in a manually driven AV is valued between the values for bus/tram/metro (-0.11) and bicycle (-0.23). In-vehicle time valuation of automatic AVs (-0.29) is more negative than for other egress modes. Also, in-vehicle time valuation of unimodal private cars is less negative (-0.14) than for AVs. The in-vehicle time valuation of a private car is almost equal to the in-vehicle time valuation of a manually driven AV. From a theoretical perspective this seems plausible, since the limited differences between these two modes in practice.

No significant results were found for the attribute ‘sharing’, a binary attribute indicating whether a traveller has to share the AV with some passengers or not. Results thus indicate that these attribute levels do not change the average utility of the multimodal trip alternative in a significant way.

Estimates for valuation of waiting time, walking time and travel costs also show significant results. Also for these attributes, only the first indicator variable was significant, indicating a linear relation with utility. For egress, waiting time for bus/tram/metro is valued 1.8 times as negative as in-vehicle time in bus/tram/metro. Walking time to the destination is valued 1.4 times as negative as in-vehicle time in bus/tram/metro as egress mode. This is slightly lower than Dutch values found by Bovy and Hoogendoorn-Lanser (2005), where waiting time and walking time are valued 2.2 and 1.6 times as negative as in-vehicle time respectively. The marginal values are comparable with ratios found by Arentze and Molin (2013) between egress waiting and walking time on the one hand and egress in-vehicle time on the other hand. They found ratios of 1.6 and 1.5 for waiting time and walking time respectively compared to in-vehicle time. Table 3 shows the calculated Willingness-to-pay (WTP) for different modes for a reduction in in-vehicle time of 10 minutes. In line with the marginal in-vehicle time values for different modes, results show that for the automatically driven AV the WTP per 10 minutes travel time savings is quite high (€2.25-€2.35) and comparable with WTP values for private car (€1.80-€1.90). WTP for manually driven AVs (€0.85-€0.95) is lower than for automatically driven AVs and private cars.

Table 3. Willingness-to-pay for different modes per 10 minutes

Part of trip	Egress mode	Willingness-to-pay per 10 minutes
Main	Private car	€1.80 - €1.90
Egress	Bus/tram/metro	€0.55 - €0.65
Egress	Bicycle	€1.45 - €1.55
Egress	Automatic vehicle: manually driven	€0.85 - €0.95
Egress	Automatic vehicle: automatically driven	€2.25 - €2.35

4. CONCLUSION AND DISCUSSION

With this study, our aim was to position automated vehicles in the transportation market and understand the sensitivity of travellers towards some of their classic travel attributes, like different travel time components and travel costs. Because there are no fully-automated vehicles currently on the market, we applied a stated preference choice experiment. Based on the results of this experiment, we can formulate different conclusions. First, the average preference for a multimodal, first class train trip using AVs as last mile transport is more positive than multimodal first class train trips with other egress modes. For multimodal second class train trips, the average preference for a trip with AVs as egress is more negative compared to other egress modes. We can therefore conclude that especially for first class train travellers, using AVs as means of transportation between the train station and the final destination can have potential. Results indicate that second class train travellers on average prefer the use of bicycle or bus/tram/metro as egress mode when making multimodal trips with train as main mode. It is however recommended to explore the role of socio-economic variables here. For example, income differences between first class and second class train travellers might partly explain the different valuations of AVs between those two traveller segments. Second, the sensitivity to in-vehicle time in a manual operated AV is almost similar to the sensitivity to in-vehicle time in a private car. This seems plausible, since the limited differences between these two modes in practice. Third, the sensitivity of travellers for in-vehicle time is considerably higher for an automatically driven AV, compared to a manually driven AV. As consequence, the willingness-to-pay for a certain travel time reduction in an automatically driven AV is considerably higher, compared to a manually driven AV. From a theoretical perspective it might be hypothesized that the time sensitivity in an automatic AV would be lower compared to a manually driven AV, since passengers can spend their travel time doing other things (like using their phone, mailing, working) instead of driving. Results suggest however that passengers, despite this theoretical advantage, might feel uncomfortable in an automated vehicle, leading to higher in-vehicle time sensitivities. Also the unfamiliarity of respondents with AVs can play a role here, might leading to a perception of unsafety to respondents. It might also be that travellers do not trust the service reliability of a fully automated vehicle yet, fearing that their trip will be delayed. Since service reliability is not incorporated explicitly as attribute in our study, respondents therefore might have valued the in-vehicle time sensitivity higher in fully automated vehicles. These results indicate the possible relevance of incorporating psychological concepts, like attitudes, when exploring preferences of travellers for automated vehicles by using hybrid choice models. Since automated driving is a very new and innovative way of transportation, the classic instrumental attributes like travel time and costs do not tell the whole story. In Yap et al. (2015, *in press*), the estimated discrete choice model has been expanded, thereby incorporating these attitudes and socio-economic variables explicitly.

Two recommendations for further research can be mentioned. First, we estimated only standard multinomial logit models in this study. We can justify this choice, since our aim was to perform a first exploration of preferences of travellers regarding classic travel attributes. Since our aim was not to use the estimated model for demand prediction purposes, the estimation of more complex models is not deemed necessary. However, it is certainly recommended to expand the current model to a more complex model in a follow-up study. For example, mixed logit models could be estimated, where corrections can be applied for the correlation between the first class and second class train alternative of a certain multimodal trip alternative, thereby also correcting for panel effects during the estimation. Estimated mixed logit models can also give more insight whether taste heterogeneity between different respondents exists. Second, in our study we only explored preferences of travellers for using the automated vehicle in the activity-end of a multimodal trip. In practice, demand will be more clustered at the activity-end of a trip, compared to the home-end of a trip. This higher activity density on the activity-end of the trip makes a first implementation of AVs as last mile transport at the activity-end of a trip more likely from an economic point of view. Therefore, we decided to explore this part of the trip first. However, exploring preferences for using AVs at the home-end of the trip is recommended. Because of differences in car-availability and network knowledge between the home-end and activity-end of the trip, different sensitivities might be expected.

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